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# Real time condition monitoring of hydraulic brake system using naïve bayes and bayes net algorithms

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**Abstract.** The vehicles usage is increasing day by day due to the recent, technological development in the automotive field. In a competitive global market in order to survive, the reliability needs to be ensured, through a proper monitoring system. Brake system is one such control component, in which much focus is very much essential. An efficient brake system should provide reliable and effective performance in order to ensure the safety. If it is not properly monitored, it may lead to a serious catastrophic effect such as accidents, brake down, etc. Hence, the brake system needs to be monitored continuously. In this study, an experimental investigation was carried out for monitoring the brake system using vibration signals. An experimental setup which resembles the brake system was fabricated. The vibration signals were acquired under various brake condition such as good and faulty. From the acquired vibration signals, the features were extracted using statistical and histogram feature extraction techniques and feature selection was carried out. The selected features were then classifieds using a Naive Bayes and Bayes Net a classifier. The classification accuracy of all the algorithms were compared for finding the best feature classifier model for monitoring the brake condition.

## 1. Introduction

The brake system of an automobile is one of the most important safety systems which is used to stop at moments and slow down the vehicle. in order to avoid an accidents. Hence, brakes should be regularly inspected, through the trusted repair facility, test drive, visual inspection, measuring pad thickness for finding pad wear etc. Unless otherwise there is a warning or a monitoring system the people will not mind about the condition nowadays. Hence, it is very important that the brake components must be monitored for faults. Many researchers are performing the condition monitoring (CM) study on the systems for diagnosing faults. CM emphases on numerous parameters in which the substantive changes indicating the development of a fault. This CM increase extends the useful lifespan of equipment by identifying troublesome areas before they cause major issues. Fault detection is a subfield of condition monitoring which anxieties itself with monitoring a system, identifying when a fault has arisen and perceiving the type of fault. There are two fault detection techniques namely signal processing based fault detection (SPBFD) and model based approach (MBA) which are mostly used for the fault diagnosis study. In the MBA some knowledge based models are used to decide about the fault manifestation. In SPBFD, some statistical processes are used to abstract the information about the fault. SPBFD is a field concerned with finding faults arising on rotating devices and machinery such as presses, pumps, electric motors, brakes, and internal combustion engines, in which the vibration is inevitable. These vibrations can be cast-off for finding the condition of the mechanical components. In this study SPBFD approach has been focused for the brake fault diagnosis study.

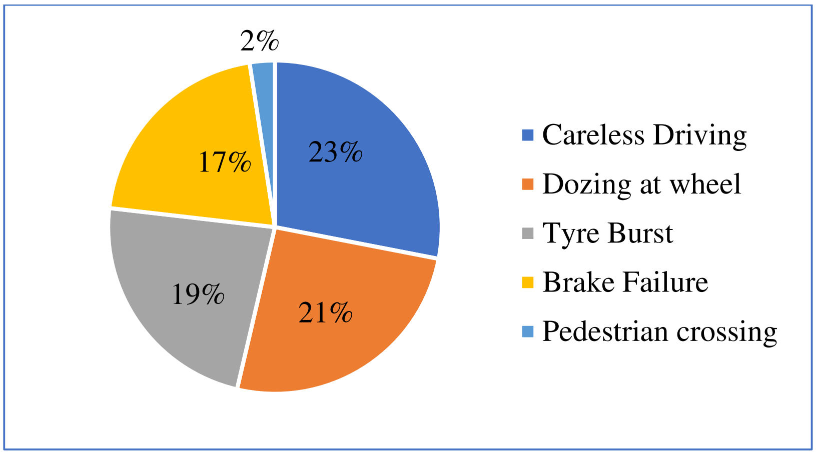


**Figure 1.** Details of major accident causes

The frequent application of brake causes faults in nature [1,2]. In recent years accident due to brake failures is increasing. Figure 1 shows the details of major causes. According to the analysis report from figure 1 the monitoring of brake failures no such automated systems are available in low and medium level LMVs. In safety point of view, the brake health should be ensured. In this study, an effort has been made to develop a monitoring model for diagnosing the brake faults. In recent years, the vibration signal has been focused in many fault diagnostic study. The hydraulic brake system is producing the vibration under different operating conditions. The produced vibration signatures are directly related with the various fault conditions has been considered for the learning process in this study.

The statistical and histogram feature analysis has been studied for many applications. The features can be excavated from the raw signals using various techniques like visual basic code, LabVIEW graphical program, and MATLAB. In this study, a novel LabVIEW graphical program was used for quarrying the features. Feature selection is necessitated in order to reduce the computational complexity. Suggested features were then used for feature classification. Classification is a feature based supervised learning.

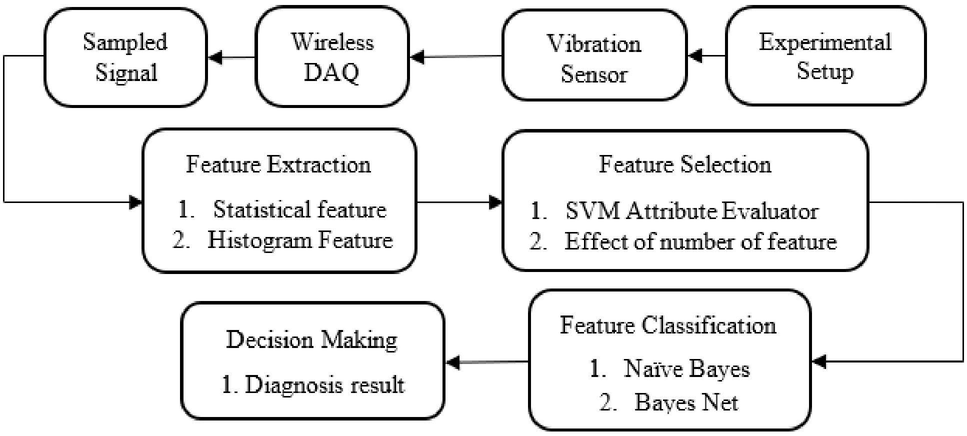


**Figure 2.** Flow Chart – Brake fault diagnosis procedure

Many learning algorithms such as decision tree (Gearbox fault diagnosis) [3], best first tree (Brake fault diagnosis) [4], Random Forest (Engine) [5], Bayes and Naïve Bayes (Pump fault diagnosis) [6], Support Vector Machine (Rolling Element Bearing and brake fault diagnosis ) [7, 8], K Star (Brake fault diagnosis and tool condition monitoring) [9, 10], Fuzzy (Centrifugal pump) [11], Logit Boost (Brake fault diagnosis) [12] were reported for many fault diagnosis applications including brake failures. In these studies, the possibility for implementing in real time with real time experiments is a huge challenge for the researchers. In this study, a real time brake health monitoring has been initiated for monitoring the brake conditions. Figure 2 shows the methodology for monitoring the condition of the hydraulic brake system.

## 2. Experimental Study

A commercial passenger vehicle (Maruti Zen) brake system was considered for the experimental study (Figure. 3). The real vehicle was used for the test. A fabricated setup with free roller was used to drive the wheel. The drive shafts were allowed to run at a constant speed (331 rpm) over the free wheel on the

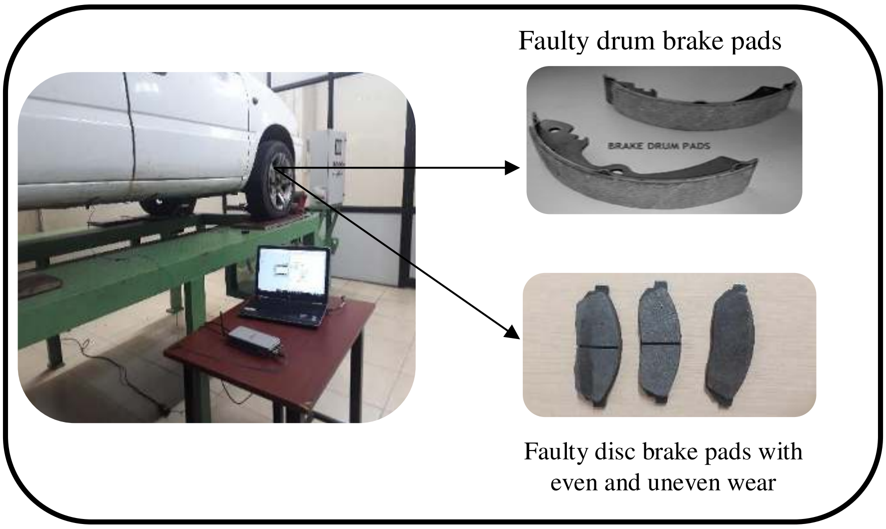


**Figure. 3.** Experimental Setup – Hydraulic Brake system

test setup. Vibration signals were acquired using a piezoelectric type shear uniaxial accelerometer (500 g range, 10.26 mV/g sensitivity) and a wireless data acquisition hardware (DAQ - Model NI 9234, 4 channel, 51.2 kilo Samples /sec) through a LabVIEW graphical program. The following frequently occurring faults namely, Inner brake pad wear in disc brake, both inner and outer pad wear in disc brake, uneven wear in inner brake pad, uneven wear in inner and outer brake pad, reservoir leak, oil spill on the disc and a good condition brake pad were considered for the simulation. Once the faults were simulated, the vibration signals were captured from the LMV brake system with the following settings:

1) *Sample length:* 12000 chosen arbitrarily
2) *Observation frequency:* 25 *kHz*
3) *Number of samples:* 65
4) *Wheel speed:* 331 rpm

## 3. Result and Discussion

### *3.1. Feature Extraction*

### *3.1.1 Statistical Feature Extraction*

The vibration signal was acquired under different fault condition from the experimental test setup. The acquired vibration signals were extracted using various statistical feature extraction techniques. Table 1 shows the sampled statistical features extracted from raw vibration signal. After the feature extraction, the IWSS attribute evaluator and ranker search feature selection method was carried out. And the selected features were classified using different classification techniques such as Naive Bayes and Bayes Net a classifier.

Table 1: Sampled Statistical Feature extracted from raw vibration signal

| **Feature** | **Values** | **Feature** | **Values** |
|---|---|---|---|
| Mean | 0.05223 | Maximum | 0.141155 |
| Standard Deviation | 0.412191 | Minimum | 1.836311 |
| Variance | 0.169901 | Range | -1.39755 |
| Kurtosis | 3.233003 | RMS | 3.233864 |
| Median | 0.046706 | Impulse factor | 0.41547 |
| Mode | 0.138532 | Shape factor | 35.15817 |
| Skewness | 0.05223 | K factor | 7.954618 |
| Standard Error | 0.762931 | Total | 12000 |
| Sum | 626.7599 | | |

### *3.1.2. Histogram Feature Extraction*

A histogram shows plot the range of variation in a better way. The information derived from a histogram plot can be used as features in the fault diagnosis. The vibration from the brake system will give better information for the histogram analysis. The histogram features can also be extracted using visual basic macro code and Micro soft office excel**.** Figure. 4 shows the sample extracted histogram feature from the test setup under various fault and good conditions of the hydraulic brake system. The bin range for the histogram plot was calculated from the minimum maximum and value of the signal. From the acquired vibration signal totally 44 bins were extracted.

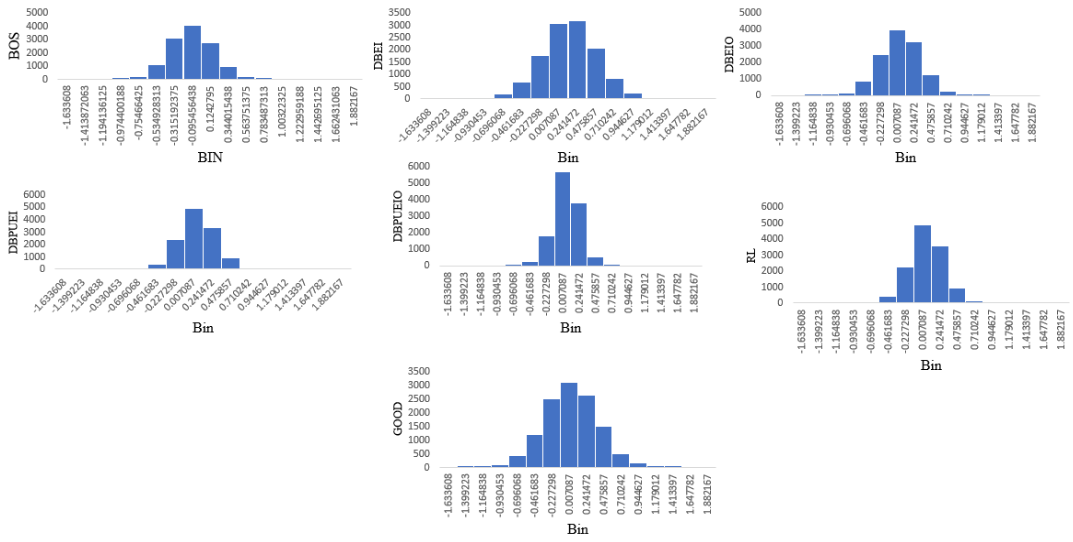


**Figure 4**. Sample histogram features

### *3.2. Feature Classification*

3.2.1 *Bayes Net* (BN)

Bayesian network comprises of a set of variables, $C = \{B_1, B_2, . . ., B_N\}$ and a set of coordinated edge A, between variables, which frame a Directed Acyclic Graph (DAG) D = (C, A) where a joint distribution of factors is spoken by the result of contingent dispersions of every variable given its folks. The selected histogram and statistical features were classified using Bayes Net. Table 2 shows the overall classification accuracy of BN classifier. Based on table 2 statistical feature gives maximum classification accuracy 90.55% (549 out of 550 data points) compare to histogram. The histogram produced classification accuracy as 78.85% (425 out of 455 data points).

Table 2 Overall Classification accuracy

| Features | Classification accuracy (%) | |
|---|---|---|
| | Bayes Net | Naive Bayes |
| Statistical | 90.55 | 89.23 |
| Histogram | 78.85 | 71.06 |

Table 3(a) Misperception Matrix for Bayes Net (Statistical)

| *Category* | ***a*** | ***b*** | ***c*** | ***d*** | ***e*** | ***f*** | ***g*** |
|---|---|---|---|---|---|---|---|
| ***a*** | 51 | 14 | 0 | 0 | 0 | 0 | 0 |
| ***b*** | 15 | 50 | 0 | 0 | 0 | 0 | 0 |
| ***c*** | 0 | 0 | 64 | 1 | 0 | 0 | 0 |
| ***d*** | 0 | 0 | 0 | 57 | 0 | 5 | 2 |
| ***e*** | 0 | 0 | 0 | 0 | 64 | 0 | 1 |
| ***f*** | 0 | 0 | 0 | 1 | 0 | 64 | 0 |
| ***g*** | 0 | 0 | 0 | 4 | 0 | 0 | 61 |

Table 3(b) Misperception Matrix for Naïve Bayes (Statistical)

| *Category* | ***a*** | ***b*** | ***c*** | ***d*** | ***e*** | ***f*** | ***g*** |
|---|---|---|---|---|---|---|---|
| ***a*** | 50 | 15 | 0 | 0 | 0 | 0 | 0 |
| ***b*** | 16 | 49 | 0 | 0 | 0 | 0 | 0 |
| ***c*** | 0 | 0 | 64 | 0 | 0 | 0 | 0 |
| ***d*** | 0 | 0 | 1 | 54 | 0 | 8 | 2 |
| ***e*** | 0 | 0 | 0 | 0 | 65 | 0 | 0 |
| ***f*** | 0 | 0 | 0 | 4 | 0 | 61 | 0 |
| ***g*** | 0 | 0 | 0 | 2 | 0 | 0 | 63 |

a - GOOD (Brake without any fault); b- DBPEI (Disc Pad Wear (Even) Inner); c – DBPEIO (Disc Pad Wear (Even) Inner & Outer); d – DBPUEI (Disc Pad Wear (Uneven) Inner); e – DBPUEIO (Disc Pad Wear (Uneven) Inner & Outer); f – BOS (Brake Oil Spill); g - RL (Reservoir Leak).

Misperception details are presented as misperception matrix. Table 3(a) shows the misperception matrix for Bayes Net. In the misperception matrix, the first-row first element (A) represents the total number of data points corresponding to ‘‘GOOD(GD)’’ condition of the brake system. The first element in the first column(A) represents how many are correctly classified as *‘A’* condition. Among the 65 data points 51 are correctly classified. 14 data point was misclassified as “Disc Pad Wear Even Inner (DBPEI)” belongs to *‘B’* condition. The same way the classification accuracy can be calculated

#### *3.2.2. Naive Bayes*

The Naïve Bayes (NB) algorithm is a classification algorithm in light of Bayes rule, which accepts the independent attributes. The estimation of this presumption is that it significantly rearranges the representation of *P(X/Y)* and the issue of assessing it from the training data. From the acquired vibration signal 60% of data can be used for training and 40% of data can be used for testing. The selected histogram and statistical features were classified using Bayes Net. Table 2 shows the overall classification accuracy of BN classifier. Based on table 2 statistical feature gives maximum classification accuracy 89.23% (406 out of 550 data points) compare to histogram. The histogram produced classification accuracy as 71.06% (383 out of 455 data points).

## 4. Comparative study

The effect of speed has also been carried out with the proposed BN and NB algorithm for validating the results. In this study, constant speed and constant load was used for finding the best feature and algorithmic model. The proposed feature classifier model has been tested under one more speed and the validation results have been given in Table 4(a) & 4(b). The results show that the vibration clearly distinguishable at higher speed because of the application of brake force which causes more vibration. The comparative study shows that the statistical feature with Bayes net produced better classification accuracy 90.55% compare to the other classifiers.

**Table 4(a)**: Comparative study for effect of speed with different classifiers (Statistical)

| Effect of speed (rpm) | Classification Accuracy % | | | |
|---|---|---|---|---|
| | **BN** | **NB** | **SVM** | **ANN** |
| **331** | 90.55 | 89.23 | 85.49 | 85.93 |
| **276** | 84.17 | 85.49 | 81.06 | 83.23 |

**Table 4(b)**: Comparative study for effect of speed with different classifiers (Histogram)

| Effect of speed (rpm) | Classification Accuracy % | | | |
|---|---|---|---|---|
| | **BN** | **NB** | **SVM** | **ANN** |
| **331** | 78.85 | 71.06 | 73.17 | 75.49 |
| **276** | 73.09 | 68.85 | 72.49 | 71.06 |

## Conclusion

In the paper, the statistical and histogram feature extraction techniques were discussed for the hydraulic brake fault diagnosis study through the vibration signal. classifiers were used for classifying the faults. The vibration signals occurred under all simulated conditions was acquired using a piezoelectric type accelerometer. Using statistical and histogram feature extraction techniques the acquired vibration signals were extracted. The feature selection was carried out using the IWSS attribute evaluator and ranker search feature selection method. Then the selected features were classified using Bayes net and Naïve bayes classifiers. Compare to histogram feature statistical feature produced maximum classification accuracy. The experimental study shows that the statistical feature with Bayes net produced better classification accuracy 90.55% compare to the other classifiers. This study can be extended on a real road condition for monitoring the health status of the hydraulic brake system. This detailed investigation will also provide a pathway for making and on-board diagnostic (OBD) module for finding the brake related faults well in advance

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